What is claimed is:

1. A method for automatically segmenting lung nodules in a three-dimensional (3D) Computed Tomography (CT) volume dataset, comprising the steps of:

receiving an input corresponding to a user-selected point near a boundary of a nodule;

constructing a model of the nodule from the user-selected point, the model being a deformable circle having a set of parameters ß that represent a shape of the nodule;

estimating continuous parts of the boundary and discontinuities of the boundary until the set of parameters ß converges, using dynamic programming and Expectation Maximization (EM); and

segmenting the nodule, based on estimates of the continuous parts of the boundary and the discontinuities of the boundary.

2. The method of claim 1, wherein the set of parameters ß = $[O, s]^T$, O being a position of the model, s being a scale of the model, and T being a transpose of a vector corresponding to the position O and the scale s of the model.

3. The method of claim 2, further comprising the step of representing the boundary as a sum B, where $B=(\bigcup_i B_{ci})\bigcup(\bigcup_i B_{dj})$, B_{ci} represents continuous parts of the boundary and B_{dj} represents discontinuities of the boundary.

4. The method of claim 3, wherein said estimating step includes the steps of;

estimating the continuous parts B_{ci} of the boundary based on a Maximum A-posteriori (MAP) estimate according to an equation B_{ci} = arg maxB_{ci} $p(B_{ci}\xi I,\ ß)$, I being a slice from the 3D CT volume dataset;

estimating a MAP density as $p(B_{ci}\xi I,\ ß) = 1/z \exp(E_ß(B_{ci}))$, $E_ß(B_{ci})$ being a sum of internal shape and external image energies, and z being a normalization constant;

minimizing the sum of internal shape and external image energies $E_ß(B_{ci})$ using a time-delayed discrete dynamic programming method;

connecting the continuous parts B_{ci} of the boundary to obtain an estimate of the discontinuities B_{dj} of the boundary; and

updating the set of parameters ß, based upon a circle fitting method being applied to the continuous parts B_{ci} and the discontinuities B_{dj} of the boundary.

5. The method of claim 1, wherein said constructing step comprises the step of increasing a radius of the deformable circle until the radius contacts high gradient points in the 3D CT volume dataset.

6. The method of claim 5, further comprising the step of pre-processing a region-of-interest that encompasses the user-selected point using an Expectation Maximization (EM) based method, so as to classify and remove a calcification from the region-of-interest.

7. The method of claim 6, wherein said pre-processing step removes the high gradient points that result from the calcification of the nodule.

8. A method for automatically segmenting lung nodules in a three-dimensional (3D) Computed Tomography (CT) volume dataset, comprising the steps of:

receiving an input corresponding to a user-selected point near a boundary of a nodule;

constructing a model of the nodule from the user-selected point, the model being a deformable circle having a set of parameters ß that represent a shape of the nodule, where ß = $[O, s]^T$, O being a position of the model, s being a scale of the model, and T being a transpose of a vector corresponding to the position O and the scale s of the model;

representing the boundary as a sum B, where $B = (\bigcup_i B_{ci}) \bigcup (\bigcup_i B_{dj})$, B_{ci} represents continuous parts of the boundary and B_{dj} represents discontinuities of the boundary;

estimating the boundary, wherein said estimating step includes the steps of;

estimating the continuous parts B_{ci} of the boundary based on a Maximum A-posteriori (MAP) estimate according to an equation B_{ci} = arg maxB_{ci} $p(B_{ci}\xi I, ß)$, I being a slice from the 3D CT volume dataset;

estimating a MAP density as $p(B_{ci}\xi I, ß)$ = 1/z exp($E_ß(B_{ci})$), $E_ß(B_{ci})$ being a sum of internal shape and external image energies;

minimizing the sum of internal shape and external image energies $E_ß(B_{ci})$ using a time-delayed discrete dynamic programming method;

connecting the continuous parts B_{ci} of the boundary to obtain an estimate of the discontinuities B_{dj} of the boundary;

updating the set of parameters ß, based upon a circle fitting method being applied to the continuous parts B_{ci} and the discontinuities B_{dj} of the boundary;

repeating said step of estimating the boundary until the set of parameters ß converges; and

segmenting the nodule, based on estimates of the continuous parts of the boundary and the discontinuities of the boundary.

9. The method of claim 8, wherein said constructing step comprises the step of increasing a radius of the deformable circle until the radius contacts high gradient points in the 3D CT volume dataset.

10. The method of claim 9, further comprising the step of pre-processing a region-of-interest that encompasses the user-selected point using an Expectation Maximization (EM) based method, so as to classify and remove a calcification from the region-of-interest.

11. The method of claim 10, wherein said pre-processing step removes the high gradient points that result from the calcification of the nodule.

12. A program storage device readable by machine, tangibly embodying a program of instructions executable by the machine to perform method steps for automatically segmenting lung nodules in a three-dimensional (3D) Computed Tomography (CT) volume dataset, said method steps comprising:

receiving an input corresponding to a user-selected point near a boundary of a nodule;

constructing a model of the nodule from the user-selected point, the model being a deformable circle having a set of parameters ß that represent a shape of the nodule;

estimating continuous parts of the boundary and discontinuities of the boundary until the set of parameters ß converges, using dynamic programming and Expectation Maximization (EM); and

segmenting the nodule, based on estimates of the continuous parts of the boundary and the discontinuities of the boundary.

13. The program storage device of claim 12, wherein the set of parameters ß = $[O, s]^T$, O being a position of the model, s being a scale of the model, and T being a transpose of a vector corresponding to the position O and the scale s of the model.

14. The program storage device of claim 13, further comprising the step of representing the boundary as a sum B, where $B = (\bigcup_i B_{ci}) \bigcup (\bigcup_i B_{dj})$, B_{ci} represents continuous parts of the boundary and B_{dj} represents discontinuities of the boundary.

15. The program storage device of claim 14, wherein said estimating step includes the steps of;

estimating the continuous parts B_{ci} of the boundary based on a Maximum A-posteriori (MAP) estimate according to an equation B_{ci} = arg maxB_{ci} $p(B_{ci}ξI$, ß), I being a slice from the 3D CT volume dataset;

estimating a MAP density as $p(B_{ci}ξI$, ß) = 1/z exp(Eß(B_{ci})), Eß(B_{ci}) being a sum of internal shape and external image energies, and z being a normalization constant;

minimizing the sum of internal shape and external image energies $E_ß(B_{ci})$ using a time-delayed discrete dynamic programming method;

connecting the continuous parts B_{ci} of the boundary to obtain an estimate of the discontinuities B_{dj} of the boundary; and

updating the set of parameters ß, based upon a circle fitting method being applied to the continuous parts B_{ci} and the discontinuities B_{dj} of the boundary.

16. The program storage device of claim 12, wherein said constructing step comprises the step of increasing a radius of the deformable circle until the radius contacts high gradient points in the 3D CT volume dataset.

17. The program storage device of claim 16, further comprising the step of pre-processing a region-of-interest that encompasses the user-selected point using an Expectation Maximization (EM) based method, so as to classify and remove a calcification from the region-of-interest.

18. The program storage device of claim 17, wherein said pre-processing step removes the high gradient points that result from the calcification of the nodule.